Grinding Burn Prediction with Artificial Neural Networks based on Grinding Parameters

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***Abstract*—Cylindrical grinding is an important process in the manufacturing industry. During this process, the problem of grinding burn may appear, which can cause the workpiece to be worthless.**

In this work, a machine learning neural network approach is used to predict grinding burn based on the process parameters to prevent damage. A small dataset of 21 samples was gathered at a specific machine, grinding always the same element type with different process parameters. Each workpiece got a label from 0 to 3 after the process, indicating the severity of grinding burn. To get a robust neural network model, the dataset has been scaled by augmentation controlled by grinding experts, to generate more samples for training a neural network model.

As a result, the model is able to predict the severity of grinding burn in a multiclass classification and it turned out that even with little data, the model performed well.

***Index Terms*—External Cylindrical Grinding, Grinding Burn, Quality Prediction, Grinding Parameters, Neural Network, Industry 4.0.**

I. Introduction

Grinding is like turning, drilling and milling one of the most important process in the manufacturing industry. It is a process that removes material from the surface of a workpiece with a grinding wheel that rotates at high speed. Grinding machines vary from simple surface grinding with one grinding wheel to complex machines with more axes, more grinding wheels and on-line measurement which introduced intelligence in the last generation of grinding machines. There are machines, they do surface grinding, where material from flat workpieces is removed and cylindrical grinding machines, where material from rotating workpieces is removed.

The performance requirements in the industry are always increasing. The manufacturing industry demands shorter cycle times, minimum human interaction, minimum set-ups, minimum number of machines and workshop space [1]. To fulfill these production requirements, grinding parameters like grinding wheel speed or infeed must be set optimally to maximize the production throughput. Depending on these parameters, the process generates grinding heat which can cause thermal damage. Burning, cracking and or undesirable residual stresses are the most common damages in grinding. [2]

Grinding itself is a complex process to understand. Due to the fact that grinding grits have an irregular geometry, cutting depths can vary from grit to grit, which results in irregular cutting geometry. Furthermore, many variables are involved what makes it even harder to choose parameters to get the desired results.

In this paper, we focus on grinding burn, because it is the major limitation in precision grinding of steel and has a deleterious effect on fatigue life and stress corrosion behavior of produced workpieces [3]. The goal of this paper is to predict grinding burn based on the given grinding parameters with an artificial neural network.

The structure of this work is as follows. In the first section, we introduce the topic grinding and the problem of grinding burn. In Section II the related work to this topic is described. In Section III, it will be described why such an intelligent grinding burn prediction system is needed. Section IV describes the parameters we use to train the artificial neural network based on expert analysis. Section V describes the prediction model we use, which includes the dataset and the artificial neural network architecture. Finally, we evaluate our prediction model in section VI and give a conclusion and outlook in the last section.

II. Related Work

In the past, a couple of research papers were published about the use case of grinding burn prediction with neural networks.

In the work from Godoy Neto et al. in [4], they used acoustic emission and vibration signals to monitor grinding burn in surface grinding. The acquisition of the vibration signals and acoustic emission was done by means of an oscilloscope with a sampling rate of 2MHz. Data was collected from 13 tests. After the measurement, they choose frequency bands which are more strongly related to grinding burn and used the RMS value as the input for the neural network. The result of one workpiece was classified into one of the three groups: No burn, burn and high surface roughness. They trained different models with different frequency bands. It turned out that the best model had two frequency bands for acoustic emission and two frequency bands for vibration signals as inputs. It had an accuracy of 98.3% on the validation set. In this work, we try to achieve similar results with different input parameters for external cylindrical grinding. Furthermore, we want to determine the severity of grinding burn with multiclass classification.

In [5], Ribeiro et al. they used piezoelectric diaphragms (PZT) to monitor the surface condition of a workpiece. A PZT sensor is a low-cost alternative to the acoustic emission sensor. Like in [4], raw signals were collected via an oscilloscope at a sampling rate of 2MHz. To compare it with acoustic emission, they collected also signals from an acoustic emission sensor. Measurements were taken from 7 tests. Each test was carried out with the same grinding parameters, except one, the depth of cut. They also chose frequency bands which are more related to grinding burn and surface roughness. To assess the condition of a workpiece, root-mean-square deviation (RMSD) indices of the frequency bands were used, so no neural network was applied. The evaluation has shown that the PZT acquired similar results as the acoustic emission sensor. The difference to our work is also that we view on different parameters to measure grinding burn and that we use a neural network instead of the RMSD values.

In [6], Bai et al. compared feed forward neural networks, least squared support vector machines, deep restricted Boltzmann machines and stack autoencoders to predict quality in a manufacturing process. The dataset consisted of 19 process parameters, some are adjustable parameters and some non-adjustable, and one quality index in a range between zero and one. The use case is not known. They trained different models via trial and error method to find the best fitting model for each architecture. Furthermore, they tried different sample sizes, 100 and 1000. It turned out that the deep restricted Boltzmann machines and stack autoencoders outperformed the other model architectures. They have also shown that the bigger the samples, the better the performance. Transferred to this work, the dataset looks similar with its adjustable and non-adjustable parameters. The differences are the use case and the quality index, which is a multiclass classification in our work.

III. Need of Grinding Burn Prediction

As mentioned in the introduction, grinding burn is the major limitation in precision grinding of steel. It has effect on fatigue life and stress corrosion behavior and it may lead to significant financial losses because grinding is the last step in the production chain [7] [5]. Since the requirements are increasing more and more, a grinding quality control system is indispensable. Also, the quality control difficulty increases because the production mode of modern enterprises changed to multi-variety and variable batch production. Conventional quality control systems are applied off-line after the grinding process in an extra production step and provide no real-time quality control and prediction which would highly minimize financial losses [8]. This leads to the need of an intelligent grinding control system with integrated grinding quality diagnosis and dynamic parameter adjustment to improve grinding quality in multi-variety and small production enterprise and assure a stable state which improves productivity, quality and most important minimize financial loss.

TABLE I
Evaluation of Grinding Parameters

Parameter	Paper	Relevance
workpiece speed	[10]	high
grinding wheel speed	[11]	very high
grinding wheel type	[11]	high
grinding type	[10]	high
coolant type	[11]	medium
infeed	[11] [10]	very high
workpiece material	-	very high
acoustic emission	[4] [12] [3] [13]	very high

IV. Parameter Selection

This section describes the relevant parameters for grinding burn, which are used by the neural network. Figure 1 depicts all the grinding machine parameter of the process. The Grinding wheel and the workpiece are rotating counterclockwise. The infeed determines how fast the grinding face removes material from the workpiece.

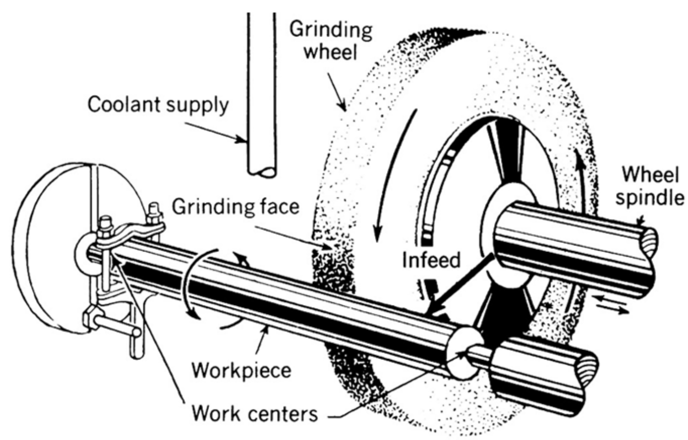

Fig. 1. External Cylindrical Grinding [9]

Based on the related work section, we noted the most common parameters used for this use case and let them evaluate by experts on their relevance. The results are given in Table I.

After collecting the grinding parameters we consulted experts from the high precision grinding institute (KSF, Furtwangen) and asks them about the relevance. According to them, the most important parameters that are most significant for causes grinding burn (very high relevance) are the grinding wheel speed, the infeed and the workpiece material. The parameters grinding type and grinding the wheel type have a high rated relevance, but they are also depending on some other parameters. The grinding type is basically the contact length between workpiece and wheel changes. Sub-parameters of grinding type are grinding wheel diameter and workpiece diameter. The grinding wheel type parameter has some sub-parameters. These are the grit kind, grit size, grit volume which is also called porosity and the bond type and bond hardness. Indirect measurable attributes of the grinding wheel are temperature, pressure and surface roughness. The coolant type parameter is rated with medium which makes it less important. In this project, we only grind dry without any coolant, which makes this parameter ignorable for the neural network. Acoustic emission is a parameter which was used in other research as almost the only input. It measures the acoustic waves of the workpiece when its internal structure get changed through grinding. Since we have no such sensor and research has been done with this parameter, we don't use it.

V. Prediction Model

A. Dataset

This section describes the dataset, which will be fed to the artificial neural network. The data was gathered by a machine operator, who ground workpieces with random grinding parameters and investigated them on their grinding burn severity. The total data consists of 21 dataset samples. Each sample holds the parameters used for grinding and a label that tells the severity of grinding burn after the process. Twelve different parameters were measured, which can be seen in Figure 2 in the input layer. Labels are given in a range from 0 to 3 (see Table II). One sample of each class is illustrated in Table III.

TABLE II
LABELING OF THE GRINDING BURN

label	grinding burn
0	no
1	hidden
2	mild
3	strong

The input parameters can be seen in Figure 2 in the input layer. The dataset was scaled by augmentation to train the network with more samples, which prevents over-fitting. Samples were generated by modifying the values of each parameter randomly in a range from plus and minus ten percent, suggested by the grinding experts. The final generated dataset has 1050 samples. The augmentation sample generation allows us to gather less real samples and therefore save a lot of time since the grinding process is a time-consuming process.

B. Neural Network

The architecture of the artificial neural network is shown in Figure 2. It has three fully connected layers in total. One input layer, one hidden layer and one output layer. The input layer has twelve neurons, based on the number of parameters given in the dataset for each sample. In the hidden layer are 64 neurons and the output layer has four neurons, one for each possible grinding burn severity.

C. Training

Given the dataset and ANN architecture, a model was trained with keras using TensorFlow as backend. The hidden layer used ReLU(rectified linear unit) as activation function and the output layer used softmax to provide probabilities for each output neuron. Weights of the model were initialized randomly. As loss function, we used categorical cross-entropy and adamax with a modified learning rate of 0.004 was used as the optimizer. 80 percent of the dataset was used for training and 20 percent for validation after each epoch. The model trained over 300 epochs.

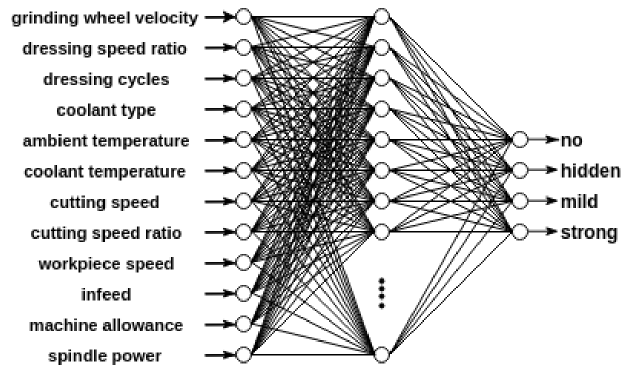

Fig. 2. Neural Network Architecture

VI. Grinding burn forecast

Figures 3 and 4 show the performance of the models training over time. The confusion matrix in Figure 5 tells that the model performs quite well. The validation loss decreased continuously and reached a minimum of 0,039 at the end of the training. The validation accuracy did also very well and reached 0,98 (98%). Only a few samples of the validation set were wrong categorized according to the confusion matrix. The model was able to distinguish perfectly between no grinding burn and grinding burn. The wrong predicted labels were only based on the severity of grinding burn.

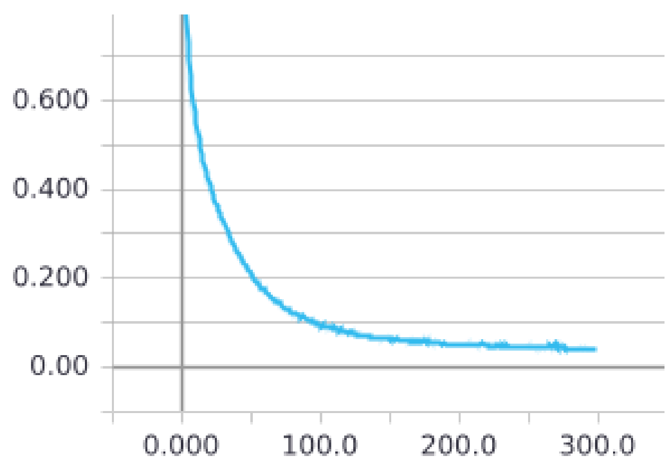

Fig. 3. Validation Loss

VII. Conclusion and Outlook

This work shows that even if there was very little data provided, the model was able to learn features corresponding to grinding burn and predict if the workpiece has grinding burn or not with given process parameters. Since 20 percent

TABLE III
DATASET

P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	**L**
60	0.6	3	1	21	29.3	60	120	184	2	500	8614	**0**
90	-0.4	6	1	21.3	28.4	90	120	276	4	1000	18266	**1**
60	0.6	0	1	21.3	30.5	60	120	184	4	1000	12655	**2**
60	-0.4	6	1	21.4	31.2	60	120	184	4	1000	18082	**3**

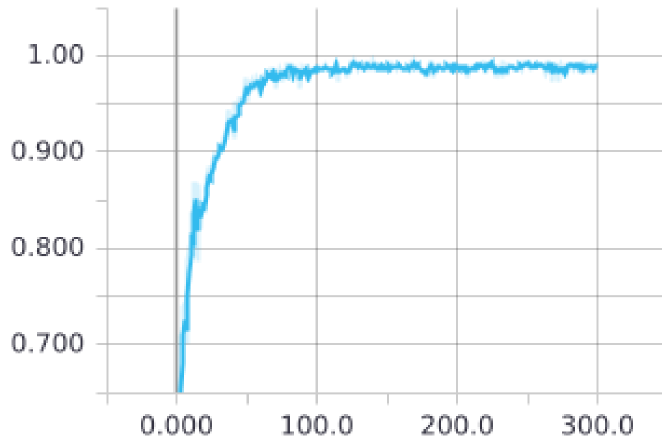

Fig. 4. Validation Accuracy

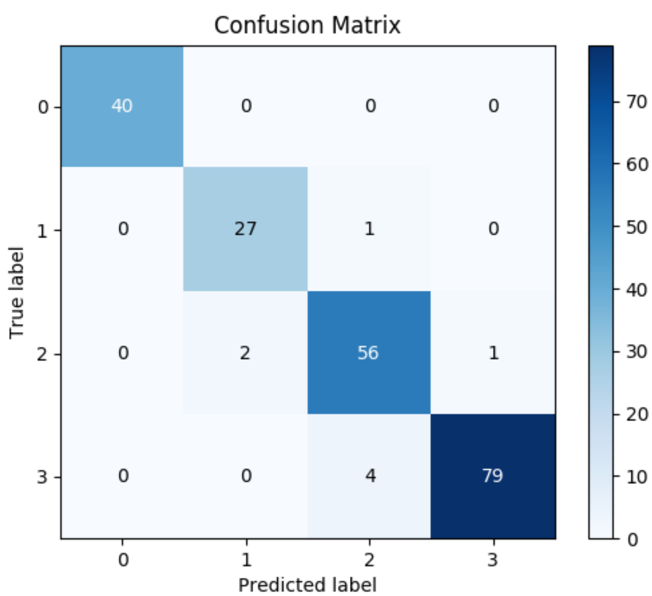

Fig. 5. Confusion Matrix

of the dataset was used for validation and only 8 out of 210 samples were predicted slightly wrong, the model proofed its potential and that this approach is worth for further research with a bigger dataset.

If the model can prove that it is still robust with a bigger dataset, it will be able to prevent financial losses and optimize the production throughput. Since in this work there is only one sample per grinding process, measurements can be expanded in the future to measure data and adapt process parameters to prevent a predicted burn while grinding, which would optimize the process even more.

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